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Ali, Abdelfatah; Raisz, David; Mahmoud, Karar; Lehtonen, Matti

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Optimal Placement and Sizing of Uncertain PVs Considering Stochastic Nature of PEVs

Abdelfatah Ali, David Raisz, *Senior Member, IEEE*, Karar Mahmoud, and Matti Lehtonen

Abstract— Recently, the penetration of photovoltaic (PV) units and plug-in electric vehicles (PEVs) has been quickly increased worldwide. Due to the intermittent nature of PV and the stochastic nature of PEVs, several operation problems can be noticed in distribution systems, including excessive energy losses and voltage violations. In this paper, an optimization-based algorithm is proposed to accurately determine the optimal locations and capacities of multiple PV units in the presence of PEVs to minimize energy losses while considering various system constraints. The proposed algorithm considers the uncertainty of PV and loads, and the stochastic nature of PEVs. Furthermore, the operational constraints of PEVs are incorporated in the optimization model: 1) arrival and departure times, 2) initial state of charge (SOC), 3) minimum preset state of charge by the owner, and 4) the time-of-use electricity tariff, and 5) different charging control schemes. The optimal PV planning model is formulated as a two-layer optimization problem that ensures an optimal PV allocation while optimizing PEV charging simultaneously. A two-layer metaheuristic method is developed to solve the optimization model considering annual datasets of the studied distribution systems. The results demonstrate the efficacy of the proposed algorithm.

Index Terms—Distribution systems; photovoltaic; plug-in electric vehicle; energy losses; optimal allocation.

I. INTRODUCTION

AS the annual demand on electricity grows, the use of distributed energy resources (DER) in power distribution systems has remarkably increased throughout the world. Photovoltaic (PV) is one of the most promising DER types. Indeed, the connection of PV units to distribution systems has several benefits to various entities, such as utility, owner, and final user. It is a fact that PV units with their active/reactive power control functionalities can improve the reliability of the power supply, enhance voltage profile, enhance power quality, and minimize energy losses [1]–[4]. Nevertheless, the

integration of such intermittent PV units with the uncertainty feature into existing systems can also lead to various technical, financial, and regulatory consequences. These consequences should be considered when deciding the highest allowed PV penetration.

Along with the rise of the PV penetration, the interest in plug-in electric vehicles (PEVs) has been intensely increasing worldwide [5], [6]. It is reported by the international energy agency that the number of various electric vehicle types was about one million in 2015 [7]. A list of countries, which are labeled as the electric vehicle initiative group, follow a future policy to grow the number of such vehicles to 20 million by 2020 [8]. PEVs are electric-based cars in which battery systems are utilized and charged during the parking period by the grid [9]–[11]. Since the average parking time of vehicles is normally more than 90% of the day [12], their battery systems can be controlled by the utility to exchange the power, thereby mitigating the technical problems of DER [13]. However, if PEVs are not properly controlled, congestion problems can result in the power lines of distribution systems [14], [15].

In the literature, numerous methods have been directed to the optimal allocation of PV in distribution systems. In [16], a planning approach based on the probabilistic has been proposed to allocate various DER types, including PV, for minimizing the energy losses in the distribution system considering system constraints. In [2], [17], [18], analytical formulae have been proposed for the optimal allocation of DER without considering the intermittent generation of renewable-based DER types. An analytical method has been proposed in [19] to allocate a single PV unit for minimizing losses with considering load variation and probabilistic PV generation. A probabilistic multi-objective algorithm has been proposed in [20] for the optimal DER planning considering the minimization of economic costs and pollutant emissions, and load uncertainties. Different metaheuristic methods have been proposed to solve the DER allocation problem, e.g. genetic algorithms [21], tabu search [22], simulated annealing [23], and ant colony optimization [24]. In [12], the role of energy storage systems as an important factor to be considered for accelerating the integration of DER to distribution systems has been highlighted. Various methods have been proposed in [25], [26] for optimizing grid integrated solar PV systems. The authors of [27] have investigated various possibilities to integrate uncertain renewable-based DER types by smart charging policies of different electric vehicle fleets.

The aforementioned literature review illustrates that considerable research work has been performed with respect to determining the optimal location and capacity of PV in

A. Ali is with the Faculty of Engineering, South Valley University, 83523 Qena, Egypt, and also with the Faculty of Electrical Engineering and Informatics, Budapest University of Technology and Economics, 1111 Budapest, Hungary (e-mail: abdefatah.mohamed@vet.bme.hu).

D. Raisz is with the Faculty of Electrical Engineering and Informatics, Budapest University of Technology and Economics, 1111 Budapest, Hungary (e-mail: raisz.david@vet.bme.hu).

K. Mahmoud is with the Department of Electrical Engineering and Automation, Aalto University, FI-00076 Espoo, Finland, and also with the Faculty of Engineering, Aswan University, 81542 Aswan, Egypt (e-mail: karar.alnagar@aswu.edu.eg).

M. Lehtonen is with the Department of Electrical Engineering and Automation, Aalto University, FI-00076 Espoo, Finland (email: matti.lehtonen@aalto.fi).

distribution systems. However, most of the proposed work is based on assumptions to simplify the planning model of PV with PEVs. Some of these methods assume either a single allocation of PV or consider deterministic models of PV and loads while they do not consider PEVs. Even the methods that consider the intermittent and uncertain nature of PV and loads, they do not consider the presence of PEVs. The existing methods do not consider the different control schemes of PEVs units, their stochastic nature, and their detailed model in the PV allocation problem. Hence, this allocation problem still requires more investigations and developments.

In this paper, an algorithm is proposed to accurately determine the optimal locations and capacities of multiple PV units to minimize energy losses considering PEVs and various system constraints. The merits of the proposed algorithm are the consideration of the uncertainty of PV and loads, and the stochastic nature of PEVs. The operation constraints of PEVs and the time-of-use (TOU) electricity tariff are considered in the optimization model. Different charging control schemes of PEVs are considered, i.e., uncontrolled charging, controlled charging, and smart charging based on the TOU electricity tariff. A two-layer optimization method, i.e. gravitational search algorithm (GSA), is formulated to solve the PV allocation problem and optimize PEV simultaneously.

II. PROBLEM FORMULATION

A. Objective function

The key objective of the proposed approach is to determine the optimal locations and capacities of PV with considering the effect of PEVs. Minimizing the total annual energy losses of the distribution system with all possible combinations of PV power and load is considered as an objective function. The probability density function (pdf) of the load demand and PV power have been split into several states to be incorporated as a multi-state variable in the planning problem. The solar irradiance and load demand are constrained within specified limits. For each state, the power losses should be calculated and weighted according to the probability of occurrence of this state during the whole planning period. Each time segment represents ΔT hours; hence, the objective function can be formulated as follows:

$$\text{Minimize } F = \sum_{t=1}^{N_t} \sum_{g=1}^{N_s} P_{loss,g}^t \times prob_{com}^t(\chi_g) \times \Delta T \quad (1)$$

in which

$$P_{loss,g}^t = P_{G,1,g}^t + \sum_{i=1}^{N_{PV}} P_{PV,i,g}^t \pm \sum_{j=1}^{N_{CS}} P_{CS,j,g}^t - P_{d,g}^t, \quad \forall g, t \quad (2)$$

where $P_{loss,g}^t$ and $prob_{com}^t(\chi_g)$ are the active power losses in the distribution system and combined probability of the load and solar irradiance at time segment t during state g , respectively; N_t and N_s are the total number of the time segments and total number of the states at each time segment (which is equal to the product of the states of PV output power and the states of the load), respectively; χ is a matrix of two columns that include all possible combinations (216 states) of the PV output power states and the load states. In χ , column 1 represents the PV output power as a percentage of the rated

power, and column 2 represents the load level as a percentage of peak load. $P_{G,1,g}^t, P_{PV,i,g}^t, P_{d,g}^t$, and $P_{CS,j,g}^t$ are the active power of the grid, PV power, demand power and charging station power, respectively. N_{PV} and N_{CS} are the number of PV units and the number of charging stations, respectively.

B. Constraints

The following equality and inequality constraints are taken into account in the optimization model.

$$P_{G,1,g}^t + \chi(g,1)P_{PV,i}^t - \chi(g,2)P_{d,i}^t \pm P_{CS,i,g}^t - V_{i,g}^t \sum_{j=1}^{NB} V_{j,g}^t \begin{bmatrix} G_{ij} \cos \delta_{ij,g}^t \\ + B_{ij} \sin \delta_{ij,g}^t \end{bmatrix} = 0, \quad \forall i \notin \phi_b, g, t \quad (3)$$

$$Q_{G,1,g}^t - \chi(g,2)Q_{d,i}^t - V_{i,g}^t \sum_{j=1}^{NB} V_{j,g}^t \begin{bmatrix} G_{ij} \sin \delta_{ij,g}^t \\ + B_{ij} \cos \delta_{ij,g}^t \end{bmatrix} = 0, \quad \forall i \notin \phi_b, g, t \quad (4)$$

$$P_{cs,i,g}^{\min,t} \leq P_{cs,i,g}^t \leq P_{cs,i,g}^{\max,t}, \quad \forall i \in \phi_b, g, t \quad (5)$$

$$P_{PV,i}^{\min} \leq P_{PV,i}^t \leq P_{PV,i}^{\max}, \quad \forall i \in \phi_b \quad (6)$$

$$\sum_{i=1}^{N_{PV}} P_{PV,i}^t \leq \sum_{i=1}^{N_l} P_{d,i,g}^t + P_{loss,g}^t, \quad \forall i \in \phi_b, g, t \quad (7)$$

$$\begin{cases} V_{1,g}^t = 1.0 \\ \delta_{1,g}^t = 0.0 \end{cases} \quad (8)$$

$$V^{\min} \leq V_{i,g}^t \leq V^{\max}, \quad \forall i \in \phi_b, g, t \quad (9)$$

$$0 \leq I_{ij,g}^t \leq I_{ij}^{\max} \quad (10)$$

$$SOC_{n,d,g} \geq SOC_{n,\min,g} \quad (11)$$

where G_{ij} , B_{ij} , $V_{i,g}^t$, and $\delta_{ij,g}^t$ are the conductance of the line ij , susceptance of line ij , voltage magnitude at bus i , and the difference of the voltage angles at bus i and j during state g and time instant t , respectively. $Q_{G,1,g}^t$ and $Q_{d,i}^t$ are the grid reactive power and demand reactive power, respectively. $P_{cs,i,g}^{\max,t}$ and $P_{cs,i,g}^{\min,t}$ are the maximum and minimum active power of the i^{th} charging station, respectively. $P_{PV,i}^{\min}$ and $P_{PV,i}^{\max}$ are the minimum and maximum power of i^{th} PV, respectively. V^{\min} and V^{\max} are the minimum and maximum voltage limits, respectively. $V_{1,g}^t$ and $\delta_{1,g}^t$ are the voltage and angle at the slack bus (bus 1), respectively. $I_{ij,g}^t$ and $I_{ij,g}^{\max}$ are the current and maximum allowable current of the line ij , respectively. NB and N_l are the number of buses and number of loads, respectively. ϕ_b is set of the PV and CS buses. $SOC_{n,d,g}$ and $SOC_{n,\min,g}$ are the state of charge (SOC) of n^{th} PEV at departure time and minimum preset SOC by the owner, respectively.

C. Modeling of PEV battery

The SOC of the battery is updated at time segment t according to its charging and it can be given as follows:

$$SOC_{n,g}^t = SOC_{n,g}^{t-1} + \eta_{ch,n} P_{ch,n,g}^t \Delta t X - \frac{1}{\eta_{dc,n}} P_{ch,n,g}^t \Delta t Y \quad (12)$$

where X and Y belong to $\{0,1\}$, in which $X.Y = 0$ because the

charging and discharging of the PEV battery cannot coexist at the same time. η_{ch} and η_{dc} are the charging and discharging efficiencies, respectively. $P_{ch,n,g}^t$ and $P_{dc,n,g}^t$ are the charging and discharging powers of n^{th} PEV, respectively.

Each PEV is charged/discharged with a certain percentage of the total optimized charging/discharging power of the charging station. This percentage depends on the capacity of the battery (C_n), SOC ($SOC_{n,g}^t$), and time left until departure (T_n). Therefore, the amount of charging/discharging power for each PEV battery n at time segment t can be computed as follows:

$$P_{ch,n,g}^t = \frac{\frac{1}{T_n}(C_n - SOC_{n,g}^t \times C_n)}{\sum_{j=1}^m \frac{1}{T_j}(C_j - SOC_{j,g}^t \times C_j)} \times P_{CS,g}^t \quad (13)$$

$$P_{dc,n,g}^t = \frac{T_n(SOC_{n,g}^t \times C_n)}{\sum_{j=1}^m T_j(SOC_{j,g}^t \times C_j)} \times P_{CS,g}^t \quad (14)$$

According to (13) and (14), the optimal active power of the charging station can be divided among the batteries of the PEVs by using the aggregator based on their current SOC and the left time until the departure. This model is used in the second layer of the optimization problem (Section V).

D. Modeling of PEV Stochastic Nature

The PEV profile is not deterministic, but it contains stochastic variables where PEVs are not connected to the distribution system at the same time. It is assumed that the PEVs are charged/discharged only at charging stations, and they begin charging/discharging from/to the distribution system as soon as their arrival. In this paper, arrival time and the initial SOC of each PEV are assumed to be random variables with a normal pdf [28]. Therefore, the pdf of daily arrival time (initial parking time) and the initial SOC of PEV battery can be given as follows:

$$f_n^t(T_A) = \frac{1}{\sigma_{T_A}^t \sqrt{2\pi}} \times \exp\left[-\frac{(T_A - \mu_{T_A}^t)^2}{2(\sigma_{T_A}^t)^2}\right] \quad (15)$$

$$f_n^t(SOC) = \frac{1}{\sigma_{SOC}^t \sqrt{2\pi}} \times \exp\left[-\frac{(SOC - \mu_{SOC}^t)^2}{2(\sigma_{SOC}^t)^2}\right] \quad (16)$$

The means and standard deviations are $\mu_{T_A}^t=18$ and $\sigma_{T_A}^t=5$ hours for daily arrival time, and they are $\mu_{SOC}^t=50\%$ and $\sigma_{SOC}^t=14\%$ for the SOC, respectively [29].

III. MODELING OF SOLAR IRRADIANCE AND LOAD

In this section, the stochastic models of PV generation and load are explained. Beta pdf is used to model hourly solar irradiance [16], [30], while the hourly load is modeled by using a normal pdf [31].

A. Modeling of Solar Irradiance

To describe the probabilistic nature of solar irradiance, a

Beta pdf is used for each time segment t , and it can be formulated as follows:

$$f_b^t(R) = \begin{cases} \frac{\Gamma(\alpha^t + \beta^t)}{\Gamma(\alpha^t)\Gamma(\beta^t)} \times (R^t)^{(\alpha^t-1)} \times (1-R^t)^{(\beta^t-1)}, & 0 \leq R^t \leq 1, \alpha^t, \beta^t \geq 0 \\ 0, & \text{otherwise} \end{cases} \quad (17)$$

where α^t and β^t are the parameters of Beta pdf at time segment t (shape parameters); Γ is the gamma function.

The Beta pdf parameters (α^t , β^t) can be computed by utilizing the mean (μ^t) and standard deviation (σ^t) of the random solar irradiance R at each time segment as follows:

$$\beta^t = (1 - \mu^t) \times \left(\frac{\mu^t \times (1 + \mu^t)}{(\sigma^t)^2} - 1 \right) \quad (18)$$

$$\alpha^t = \frac{\mu^t \times \beta^t}{1 - \mu^t} \quad (19)$$

The probability of solar irradiance for each state can be calculated as follows:

$$prob_R^t(G_s) = \int_{R_{S1}}^{R_{S2}} f_b^t(R) \cdot dR \quad (20)$$

where $prob_R^t(G_s)$ is the solar irradiance probability in state s ; R_{S1} and R_{S2} are the solar irradiance limits of state s .

Once the Beta pdf is generated for a specific time segment, the output power during the different states can be calculated for this segment as follows:

$$P_{PV_s} = N \times \frac{V_{MPP} \times I_{MPP}}{V_{OC} \times I_{SC}} \times V_{cell_s} \times I_{cell_s} \quad (21)$$

in which

$$T_{cell_s} = T_A + R_{avs} \left(\frac{N_{OT} - 20}{0.8} \right) \quad (22)$$

$$I_{cell_s} = R_{avs} \left(I_{SC} + K_i (T_{cell_s} - 25) \right) \quad (23)$$

$$V_{cell_s} = V_{OC} - K_v T_{cell_s} \quad (24)$$

where V_{MPP} , I_{MPP} , V_{OC} , I_{SC} , V_{cell_s} , I_{cell_s} , and N are the voltage at the maximum power point, current at the maximum power point, open-circuit voltage, short circuit current, cell voltage, cell current, and the number of PV modules, respectively. T_{cell_s} , T_A , R_{avs} , N_{OT} , K_i , and K_v are the cell temperature, ambient temperature, average solar irradiance, nominal operating temperature of the cell, current temperature coefficient, and voltage temperature coefficient, respectively.

B. Load Demand Modeling

The future load demand of the distribution system is uncertain at any given time segment. Therefore, a normal pdf is utilized to model the distribution of the load demand [31], as follows:

$$f_n^t(l) = \frac{1}{\sigma_l^t \sqrt{2\pi}} \times \exp\left[-\frac{(l - \mu_l^t)^2}{2(\sigma_l^t)^2}\right] \quad (25)$$

The load demand probability of each state for each time segment t can be given as follows:

$$prob_i^t(G_y) = \int_{l_{y1}}^{l_{y2}} f_n^t(l) dl \quad (26)$$

where $prob_i^t(G_y)$ is the solar irradiance probability in state y ; l_{y1} and l_{y2} are the load demand limits of state y .

C. Combined PV-load model

To generate the model of combined PV-load, the modeling of the PV power and the load represented by (20) and (26) are used. In this study, the states of solar irradiance and load are assumed to be independent. Hence, the combined probability of the solar irradiance and load can be determined by convolving the two probabilities, as given in the following:

$$prob_{com}^t(\chi_g) = prob_R^t(G_s) \times prob_i^t(G_y) \quad (27)$$

Based on (27), the model of PV-load is determined by listing all possible combinations of the PV power and the load. Therefore, the complete PV-load model is computed by:

$$\psi = \left[\left\{ \chi_g, prob_{com}(\chi_g) \right\} : g = 1 : N_s \right] \quad (28)$$

where ψ is the complete annual PV-load model; $prob_{com}(\chi_g)$ is a column that symbolizes the combined probability based on matrix χ .

IV. GRAVITATIONAL SEARCH ALGORITHM (GSA)

The GSA is a newly heuristic optimization algorithm, and it has been proposed by Rashedi *et al.* [32]. In this algorithm, the search agents are a collection of objects (masses) which interact with each other. This interaction is based on the Newtonian gravity and the laws of motion. The main idea of GSA can be described as follows:

If a system has N objects (masses) in a d -dimensional search space, the position of the i^{th} object can be given by

$$X_i = [x_i^1, x_i^2, \dots, x_i^d, \dots, x_i^q] \quad \text{for } i = 1, 2, \dots, N \quad (29)$$

where x_i^d is the position of the i^{th} object in the d^{th} dimension; q defines the space dimension of the problem, i.e. the number of decision variables.

After estimating the population fitness, the inertial mass of each object can be calculated as follows:

$$M_i(t) = \frac{m_i(t)}{\sum_{j=1}^N m_j(t)} \quad (30)$$

in which

$$m_i(t) = \frac{fit_i(t) - worst(t)}{best(t) - worst(t)} \quad (31)$$

where $fit_i(t)$ is the fitness value of i^{th} object at time instant t ; $best(t)$ is the best fitness value; $worst(t)$ is the worst fitness value. For minimization problem, $best(t)$ and $worst(t)$ can be given as follows:

$$best(t) = \min_{j \in \{1, \dots, N\}} fit_j(t) \quad (32)$$

$$worst(t) = \max_{j \in \{1, \dots, N\}} fit_j(t) \quad (33)$$

Based on Newton gravitation, at time instant t , the gravitational force that acts on object i in d^{th} dimension can be described as follows:

$$F_i^d(t) = \sum_{\substack{j \in kbest \\ j \neq i}} r_j G(t) \frac{M_i(t) \times M_j(t)}{S_{ij} + \varepsilon} (x_j^d(t) - x_i^d(t)) \quad (34)$$

where $G(t)$ is the gravitational constant at time instant t ; $M_i(t)$ and $M_j(t)$ are the inertial mass of the objects i and j , respectively; r_i is a random number in the interval $[0, 1]$; $kbest$ is a linear function that decreases over time where its initial value is N (the minimum value is 1); ε is a small number that is equal 2^{-52} ; $S_{ij}(t)$ is the Euclidean distance between object i and j and can be given as follows:

$$S_{ij}(t) = \|X_i(t), X_j(t)\|_2 \quad (35)$$

Based on the law of motion, the acceleration of the i^{th} object in d^{th} dimension at time t can be given by the following equation:

$$a_i^d(t) = \frac{F_i^d(t)}{M_i(t)} \quad (36)$$

Each iteration process, the velocity, and position of the particle can be updated according to the following:

$$v_i^d(t+1) = rand_i \times v_i^d(t) + a_i^d(t) \quad (37)$$

$$x_i^d(t+1) = x_i^d(t) + v_i^d(t+1) \quad (38)$$

where x_i^d and v_i^d are the position and velocity of the object at time t in d^{th} dimension, respectively. In this work, only agents satisfying the constraints are retained for the next generation.

It is important to mention that the gravitational constant $G(t)$ has a great effect on the performance of GSA. $G(t)$ is randomly initialized at the start and reduces overtime for controlling the search accuracy. $G(t)$ is a function of its initial value (G_0) and time (t) where G_0 is decided arbitrarily. The gravitational constant can be computed as follows,

$$G(t) = G_0 \exp\left(-\alpha \frac{t}{tmax}\right) \quad (39)$$

where α is a user-specified constant term; t is the current iteration; $tmax$ is the maximum number of iterations.

It is important to note that the main purpose of this work is to build an optimization model for the allocation problem. This optimization can be solved by any available optimization algorithm [33], [34]. We have selected GSA as it has high performance according to several previous publications, which means that it can find the global optimal solution in a fast way.

V. SOLUTION PROCESS

The block diagram of the proposed approach is described generally in Fig. 1. As shown in the figure, optimal planning of the PV in the presence of PEVs has been considered as a two-layer optimization problem that is solved using GSA. Because of the complexity of the problem, the GSA is used in both layers and called optimizer 1 for the first layer and optimizer 2 for the second layer. To attain high accuracy and low computational time, the population size and number of iterations of optimizer 1 (30, 100) are chosen to be larger than those in optimizer 2 (25, 50). The main problem and sub-problem are solved using optimizer 1 and optimizer 2, respectively.

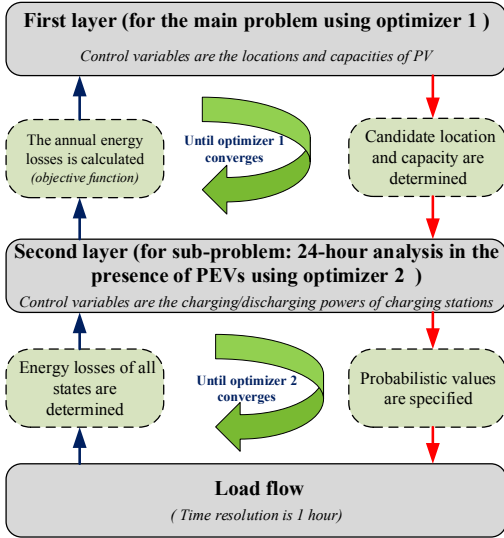


Fig. 1. The proposed approach for determining the locations and capacities of PV.

In the first layer, where it is the main problem, the optimizer 1 should determine the locations and capacities of the PV for the planning period. To do so, the optimal charging/discharging power of the charging stations should be considered. The number of PEVs connected to the distribution system is a stochastic variable. Therefore, the optimal scheduling of PEVs is a probabilistic process in practice (second layer). The outputs of the second layer, as a sub-problem for an optimal planning problem, are the probabilistic optimal charging/discharging power profiles.

To calculate the value of the objective function for each state at time segment t , load flow analysis is used. The solution process of this combinatorial problem is described in the following paragraph.

Optimizer 1 which is used in the first layer suggests candidate locations and capacities of the PV. These locations and capacities are used in the second layer to calculate the daily energy losses and the daily optimal charging/discharging power of the charging stations. It is important to note that the locations and capacities of the PV are kept fixed during the executing of optimizer 2. This procedure does not affect the searching for optimal locations and capacities of the PV, because the pdf of the PEVs will be used with each candidate location and capacity. As shown in Fig. 1, the planning problem contains an internal optimization problem as a sub-problem. Hence, in each iteration of optimizer 1, the internal optimization problem should be performed completely several times for several candidate locations and capacities of PV. In each iteration of optimizer 2, the load flow analysis should be performed several times to compute the optimal charging/discharging powers of the charging stations for each state at time segment t as well as the value of the corresponding objective function. The summation of the whole individual objective functions (at all states and time segments) is considered the objective function of the optimizer 1 (annual energy losses). This process is repeated until optimizer 1 converges.

VI. RESULTS AND DISCUSSIONS

The IEEE 33-bus distribution system has been selected to test the proposed approach as shown in Fig. 2. The line and

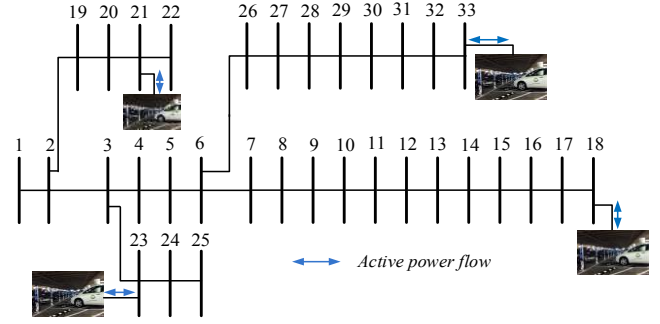


Fig. 2. Single line diagram of the 33-bus distribution system.

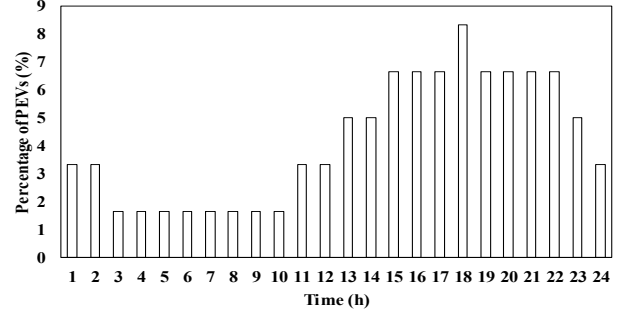


Fig. 3. Percentage of PEVs which arrive each hour with $\mu=18$ and $\sigma=5$ hours for 60 PEVs.

bus data of that system are available in [35]. Four PEV charging stations are assumed to be connected at buses (18, 21, 23, and 33) as shown in Fig. 2. Each charging station accommodates 60 PEVs. Based on the arrival time, the daily distribution of the PEVs at the charging stations follows Fig. 3, and the initial SOC of each PEV is calculated based on (16).

The PEVs of Tesla Model S with a battery capacity of 85 kWh is used in this paper [36]. Each PEV is assumed to be parked at the charging station for 12 hours (from the arrival time till the next departure time). For each state, the PEV cannot discharge to the grid (vehicle-to-grid) if its SOC is less than 75%. To ensure that the SOC of the PEV battery at the departure time is high enough, the PEV discharges to the grid (vehicle-to-grid) considering the constraint given in (11). The maximum power rate of charging/discharging has been chosen to be 0.2 of the battery capacity ($C_n=85$ kW) [37]. The PV is assumed to be operated at unity power factor. To demonstrate the effectiveness of the proposed approach, it has been tested for one, two, and three locations of PV. Furthermore, the proposed approach has been performed with and without considering the TOU electricity tariff. The planning period considered in this paper is three years and it is represented by any day within this period (24 hours). The simulation results have been performed using MATLAB.

A. Optimal Locations and Capacities of PV without Considering TOU

In this subsection, the proposed approach has been executed and compared with the base case and another approach without considering the electricity tariff. The base case and different approaches can be described as follow:

Base case: this is the reference case in which there is no PVs are connected to the distribution system and the PEVs start to charge once they arrive at the charging station with the uncontrolled charging technique.

Approach 1: in this approach, the optimal locations and capacities of the PV are determined without considering the effect of uncontrolled charging of PEVs.

Approach 2: this is the proposed approach in which the optimal locations and capacities of the PV are determined with considering the effect of PEVs. The PEVs are considered to charge/discharge with the optimal charging/discharging technique.

The outcomes of the planning problem for the different approaches are shown in Table I, and Figs. 4, 5 and 6. The results demonstrate that in the case of Approach 1 and Approach 2, there is a significant reduction in the annual energy losses by connecting the PV to the distribution grid when compared to the reference case (Base case). However, the reduction of the annual energy losses for Approach 2 is higher than Approach 1. For instance, the reductions of annual energy losses in the case of Approach 2 are 38%, 43%, and 46% for 1 PV, 2 PVs, and 3 PVs, respectively. While they are 30%, 37%, and 41% in the case of Approach 1. Note that with

TABLE I
RESULTS OF DIFFERENT APPROACHES WITH DIFFERENT NUMBERS OF PVs

Number of PVs	Applied approach	Optimal location	Optimal capacity (MW)	Energy losses (MWh)	Energy loss reduction (%)
No PVs	Base case	-	-	1793	0
1 PV	Approach 1	6	3.29	1259	30
	Approach 2	6	3.66	1116	38
2 PVs	Approach 1	6	2.41	1138	37
		14	0.84		
	Approach 2	6	2.41	1023	43
		14	0.82		
3 PVs	Approach 1	6	1.48	1062	41
		14	0.85		
		31	0.89		
	Approach 2	6	1.34	963	46
		14	0.97		
		31	1.09		

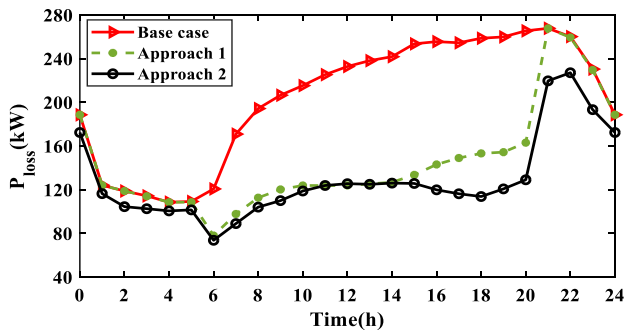


Fig. 4. Active power losses during the planning period (1 PV).

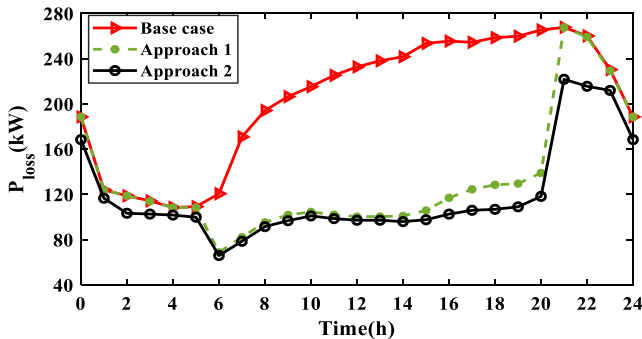


Fig. 5. Active power losses during the planning period (2 PVs).

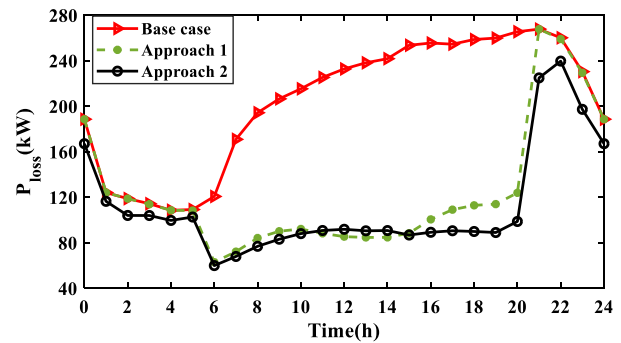


Fig. 6. Active power losses during the planning period (3 PVs).

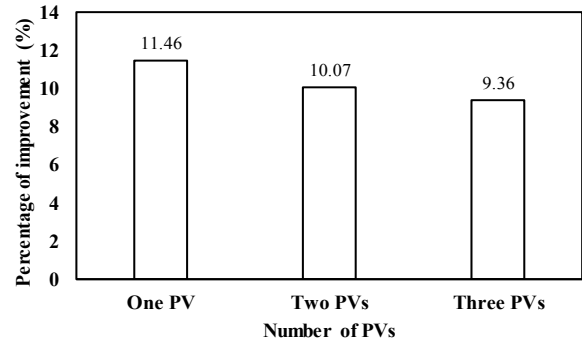


Fig. 7. Annual energy improvement in the case of Approach 2 over Approach 1.

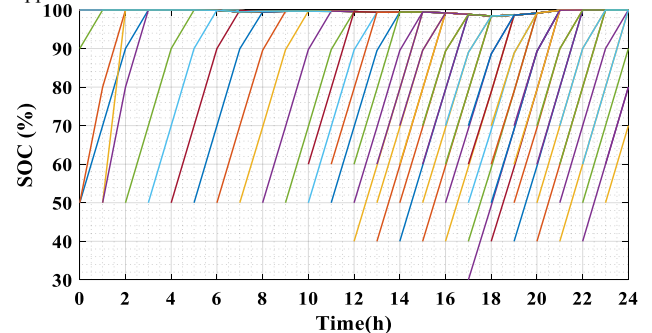


Fig. 8. SOC of PEVs using the uncontrolled charging technique in the Base case and Approach 1.

increasing the number of PVs, the reduction of annual energy losses is increased.

The improvement percentage of Approach 2 over Approach 1 is given in Fig. 7. From this figure, it can be noted that the improvement percentage depends on the number of PVs connected to the distribution system in which the improvement of Approach 2 decreases with increasing the number of PVs. The percentages of the improvement in the case of Approach 2 over Approach 1 are 11.46%, 10.07%, and 9.36% for 1 PV, 2 PVs, and 3 PVs, respectively.

The SOC of all PEVs at the charging stations with uncontrolled charging technique (in the case of Base case and Approach 1) are given in Fig. 8. To avoid results repetition, this figure is drawn one time because it is the same for 1 PV, 2 PVs, and 3 PVs in the case of Approach 1. From this figure, it can be seen that the SOC of PEVs are reached to their full state in a short period even though they will remain in the charging station for 12 hours. Because of the high changing power, the system losses are increased.

Fig. 9 shows the SOC of all PEVs at the charging stations with the optimal charging/discharging technique with different

numbers of connected PVs. The PEVs that arrive at the end of the previous day have been considered where they would continue charging at the beginning of the sample day. From the figure, we can note that the SOC of each PEV can increase/decrease based on its state (charging/discharging) to reduce the losses of the distribution system. Furthermore, the battery of each PEV at the departure time (after 12 hours from its connection to the grid) has sufficient SOC for driving (not less than 60% at departure time). These results demonstrate that the considering of PEVs with the optimal charging/discharging technique when determining the optimal location and capacity of the PVs can significantly decrease the energy losses of the distribution system. Regarding the SOC of PEVs at the other charging stations, they are similar to the charging station at bus 18 in the case of uncontrolled charging while they are different in the four charging stations in the case of controlled charging/discharging. In general, all PEVs will have SOC at the departure time as preset by the owner

If the level of SOC at departure time is set to be 65% (e.g., in the case of 3 PVs), the annual energy losses will be 968 MWh which is high compared to 963 MWh in the case of 60% (Table I). This rise in the annual energy losses is achieved by increasing the charging power to satisfy SOC level and so the available energy to be discharged is decreased. Fig. 10 shows the SOC of all PEVs at the charging stations considering

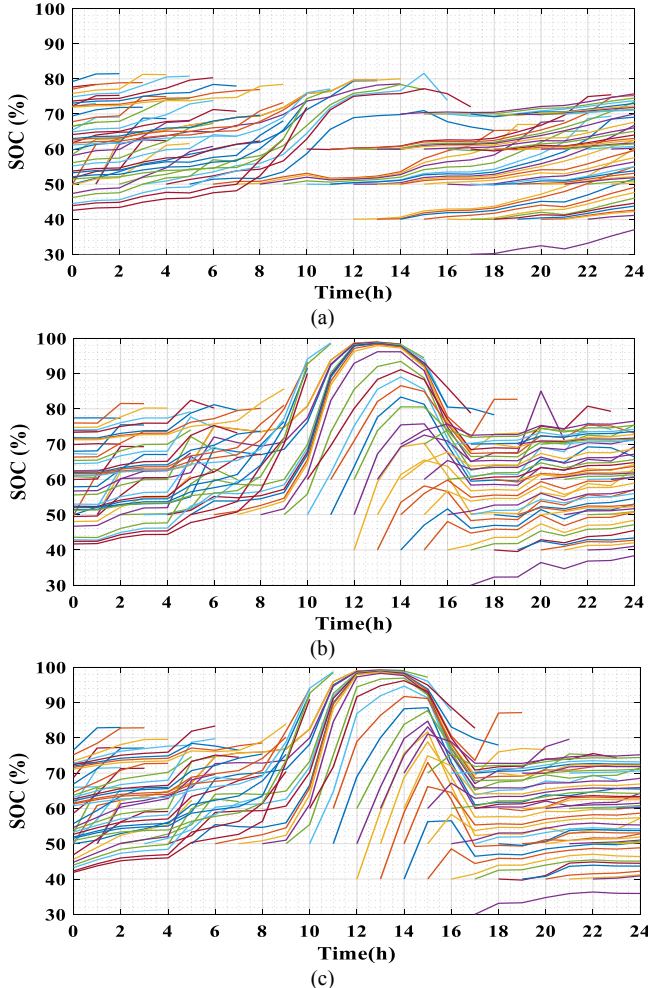


Fig. 9. SOC of PEVs using the optimal charging/discharging technique in the case of Approach 2. a) 1 PV, b) 2 PVs, and c) 3 PVs.

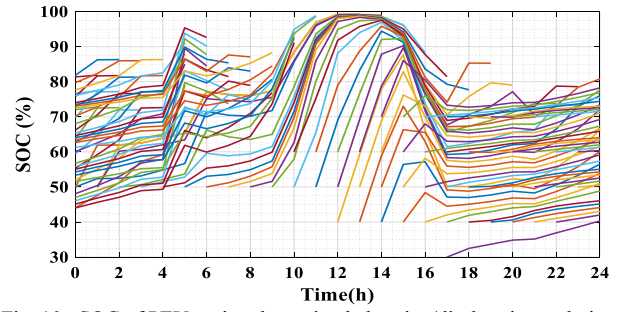


Fig. 10. SOC of PEVs using the optimal charging/discharging technique in the case of Approach 2 considering that the minimum SOC at departure time is 65% (3 PVs).

minimum SOC at departure time is 65%.

B. Optimal Locations and Capacities of PV with Considering TOU

In this subsection, four different cases have been performed using the proposed approach (considering of PEVs) with considering the effect of TOU for determining the optimal location and capacity of the PV as follows:

Case 1: Optimal locations and capacities of the PV are determined with considering PEVs in the case of the uncontrolled charging technique.

Case 2: Optimal locations and capacities of the PV are determined with considering PEVs in the case of the uncontrolled off-peak charging technique. i.e., the PEVs cannot charge during the peak period in which the electric price is high. The peak period is 16.00-22.00 h.

Case 3: Optimal locations and capacities of the PV are determined with considering PEVs in the case of uncontrolled off-peak charging and uncontrolled on-peak discharging.

Case 4: Optimal locations and capacities of the PV are determined with considering PEVs in the case of the optimal charging/discharging technique. In this case, during off-peak, maximum charging power is $0.2C_n$ power while the maximum discharging power is 60% of the maximum charging power. On the other hand, during the peak period, maximum discharging power is $0.2C_n$ while the maximum charging power is 60% of the maximum discharging power.

Table II illustrates the results of the different cases. From this table, we can note that the PV locations are the same as those in subsection A, while the PV capacities are different. Compared with the reference case (Base case), the annual energy losses are significantly decreased in the four cases. Case 4 gives better energy losses reduction than the other cases, while Case 3 is the worst case in terms of energy losses reduction. The energy losses reduction in Case 4 are 39%, 44%, and 48% for 1 PV, 2 PVs, and 3 PVs, respectively. However, they are 30%, 37%, and 41% for Case 1, 25%, 31%, and 35% for Case 2, and 23%, 28%, and 32% for Case 3, respectively. By comparing Case 4 in Table II with Approach 2 in Table I, we can note that the consideration of TOU gives a further reduction in annual energy losses.

Figs. 11, 12, and 13 show the SOC of all PEVs at the charging stations for Case 2, Case 3, and Case 4 when 3 PVs are connected to the distribution system, respectively. The SOC of PEVs in Case 1 is the same as Fig. 8, while the SOC of PEVs for Case 2, Case 3, and Case 4 when 1 PV and 2 PVs are connected to the distributions system follow the same

TABLE II
RESULTS OF DIFFERENT CASES OF THE PROPOSED APPROACH WITH
CONSIDERING TOU

Number of PVs	Applied Case	Optimal location	Optimal capacity (MW)	Energy losses (MWh)	Energy loss reduction (%)
1 PV	Case 1	6	3.59	1253	30
	Case 2	6	3.48	1347	25
	Case 3	6	3.43	1389	23
	Case 4	6	3.42	1096	39
2 PVs	Case 1	6	2.58	1132	37
		14	0.95		
	Case 2	6	2.51	1242	31
		14	0.91		
	Case 3	6	2.49	1291	28
		14	0.89		
	Case 4	6	2.36	1005	44
		14	0.99		
3 PVs	Case 1	6	1.54	1055	41
		14	0.95		
		31	0.99		
	Case 2	6	1.54	1174	35
		14	0.91		
		31	0.95		
	Case 3	6	1.51	1227	32
		14	0.89		
		31	0.94		
	Case 4	6	1.53	937	48
		14	0.96		
		31	0.90		

trend when 3 PVs are connected.

C. Optimal Locations and Capacities of PV for a larger distribution system

Here, we study the impact of the charging/discharging schemes of PEVs on the allocation results of PV for a larger distribution system (69-bus system [30]). As illustrated for the small 33-bus distribution system, the PV locations with considering different charging/discharging schemes of PEVs are the same, but their capacities are different. However, this trend is not a general one for all distribution systems. To demonstrate this fact, we allocate 3 PV units to the larger test distribution system by considering uncontrolled and controlled PEVs. As shown in Table III, the optimal PV locations are buses 11, 17, and 64 for the case of uncontrolled PEVs, while different locations are obtained for the case of controlled PEVs (buses 11, 18, and 61). It is worth noting that controlled PEVs yields higher energy loss reduction compared to uncontrolled PEVs, thanks to the consideration of optimal charging/discharging of PEVs.

VII. CONCLUSIONS

In this paper, an optimization-based algorithm has been proposed to accurately allocate multiple PV units with the presence of PEVs to minimize energy losses without violating the system constraints. The proposed optimization model also incorporates several operation constraints of PEVs. A metaheuristic method, i.e. GSA, has been developed to solve the two-layer optimization problem. The merit of the proposed algorithm is that it accurately allocates PV to minimize the objective function and optimize the PEV charging/discharging in a simultaneous manner. To demonstrate the effectiveness of the proposed algorithm, it has been compared with the existing approaches that ignore the effect of PEVs and TOU in the PV

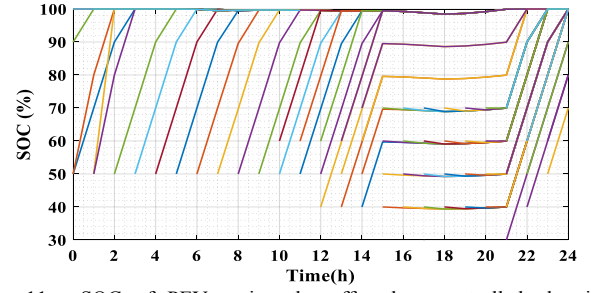


Fig. 11. SOC of PEVs using the off-peak uncontrolled charging technique for Case 2 (3 PVs).

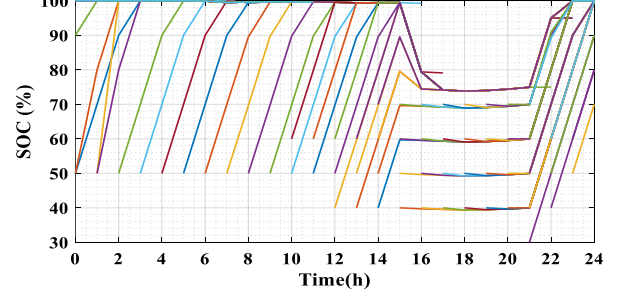


Fig. 12. SOC of PEVs using the off-peak uncontrolled charging and on-peak uncontrolled discharging technique for Case 3 (3 PVs).

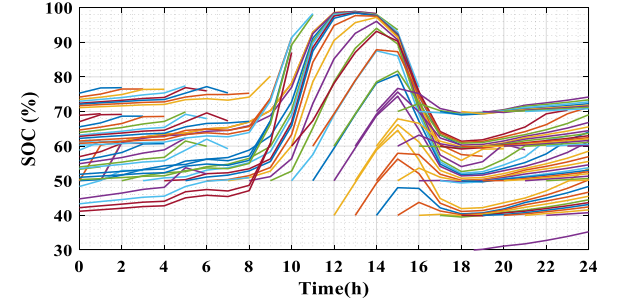


Fig. 13. SOC of PEVs using the optimal charging/discharging technique and considering TOU for Case 4 (3 PVs).

TABLE III
RESULTS OF 69-BUS DISTRIBUTION SYSTEM CONSIDERING CONTROLLED
AND UNCONTROLLED PEVS

Number of PVs	Applied approach	Optimal location	Optimal capacity (MW)	Energy losses (MWh)	Energy loss reduction (%)
No PVs	Base case	-	-	1812	-
3 PVs	Uncontrolled PEVs	11	0.88	1058	42
		18	0.45		
		64	1.93		
	Controlled PEVs	11	0.83	895	51
		17	0.50		
		61	2.31		

planning problem. Based on the calculated results, the following conclusions can be drawn:

- The proposed approach which considers the uncertainty of PVs and stochastic nature of PEVs is an effective way to accurately allocate PV units while maximizing their benefits to distribution systems.
- The charging scheme of PEVs can greatly affect the allocation results of PV (optimal locations and sizes), especially for large distribution systems.
- The benefits of the proposed approach for large-scale single PV units are higher than those of lower-scale distributed PV units.

The practical significance of the results is even more prevalent in the context where distribution system operators receive financial remuneration (as part of the system usage tariff) for the estimated losses on their networks. In such regulatory setups, the optimized PV sizes/locations and PEV schedules can be used for benchmarking the losses occurring at actual PV and PEV penetration situations. Such investigations can help in assessing whether an actual situation is beneficial or causing additional costs for the operators. In the future work, various DER types and other energy storage devices will be incorporated in the optimization model. In addition, the proposed method will be expanded to consider the demand growth, DER prices, and other technical objectives.

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Abdelfatah Ali was born in Egypt on October, 19, 1986. He received the B.Sc. degree and the M.Sc. degree in electrical engineering from Aswan University, Aswan, Egypt, in 2009 and 2013, respectively. Since 2010, he has been an Assistant Lecturer with the Faculty of Engineering, South Valley University, Qena, Egypt. He is currently working toward the Ph.D. degree at the Doctoral School of Electrical Engineering, Faculty of Electrical Engineering and Informatics, Budapest University of Technology and Economics, Budapest, Hungary. His research interests include modeling, analysis, control, and optimization of distribution systems with distributed generation and electric vehicles.

Engineering Department. His main activities include earth fault problems, and harmonic related issues and applications of information technology in distribution automation and distribution energy management.



David Raisz (M'06–SM'18) received the M.Sc. degree and the Ph.D. degree in electrical engineering from the Budapest University of Technology and Economics (BUTE), Budapest, Hungary, in 2000 and 2011, respectively. From 1999 to 2001, he joined the Graz University of Technology, Austria, as a Guest Researcher. From 2012 to 2016, he led the Power Systems and Environment Group with the Department of Electric Power Engineering, BUTE, as an Associate Professor. In 2017, he joined the Institute for Automation of Complex Power Systems within the E.ON Energy Research Center, RWTH Aachen University. He has been working on or leading more than 40 industrial and research projects.



Karar Mahmoud received the B.S. and M.Sc. degrees in electrical engineering from Aswan University, Aswan, Egypt, in 2008 and 2012, respectively. In 2016, he received the Ph.D. degree from the Electric Power and Energy System Laboratory (EPESL), Graduate School of Engineering, Hiroshima University, Hiroshima, Japan. Since 2010, he has been with Aswan University where he is presently Assistant Professor. Currently, he is a Postdoctoral Researcher at the School of Electrical Engineering, Aalto University, Finland. His research interests include Power Systems, Renewable Energy Resources, Smart Grids, Distributed Generation, and Optimization.



Matti Lehtonen received the M.Sc. and Licentiate degrees in electrical engineering from the School of Electrical Engineering, Aalto University (formerly Helsinki University of Technology), Espoo, Finland, in 1984 and 1989, respectively, and the D.Sc. degree from the Tampere University of Technology, Tampere, Finland, in 1992. Since 1987, he has been with VTT Energy, Espoo, and since 1999, he has been with the School of Electrical Engineering, Aalto University, where he is currently the Head of Power Systems and High Voltage